Improving activity recognition using a wearable barometric pressure sensor in mobility-impaired stroke patients

Massé, F ; Gonzenbach, R R ; Arami, A ; Paraschiv-Ionescu, A ; Luft, A R ; Aminian, K

Abstract: BACKGROUND Stroke survivors often suffer from mobility deficits. Current clinical evaluation methods, including questionnaires and motor function tests, cannot provide an objective measure of the patients' mobility in daily life. Physical activity performance in daily-life can be assessed using unobtrusive monitoring, for example with a single sensor module fixed on the trunk. Existing approaches based on inertial sensors have limited performance, particularly in detecting transitions between different activities and postures, due to the inherent inter-patient variability of kinematic patterns. To overcome these limitations, one possibility is to use additional information from a barometric pressure (BP) sensor. METHODS Our study aims at integrating BP and inertial sensor data into an activity classifier in order to improve the activity (sitting, standing, walking, lying) recognition and the corresponding body elevation (during climbing stairs or when taking an elevator). Taking into account the trunk elevation changes during postural transitions (sit-to-stand, stand-to-sit), we devised an event-driven activity classifier based on fuzzy-logic. Data were acquired from 12 stroke patients with impaired mobility, using a trunk-worn inertial and BP sensor. Events, including walking and lying periods and potential postural transitions, were first extracted. These events were then fed into a double-stage hierarchical Fuzzy Inference System (H-FIS). The first stage processed the events to infer activities and the second stage improved activity recognition by applying behavioral constraints. Finally, the body elevation was estimated using a pattern-enhancing algorithm applied on BP. The patients were videotaped for reference. The performance of the algorithm was estimated using the Correct Classification Rate (CCR) and F-score. The BP-based classification approach was benchmarked against a previously-published fuzzy-logic classifier (FIS-IMU) and a conventional epoch-based classifier (EPOCH). RESULTS The algorithm performance for posture/activity detection, in terms of CCR was 90.4 %, with 3.3 % and 5.6 % improvements against FIS-IMU and EPOCH, respectively. The proposed classifier essentially benefits from a better recognition of standing activity (70.3 % versus 61.5 % [FIS-IMU] and 42.5 % [EPOCH]) with 98.2 % CCR for body elevation estimation. CONCLUSION The monitoring and recognition of daily activities in mobility-impaired stoke patients can be significantly improved using a trunk-fixed sensor that integrates BP, inertial sensors, and an event-based activity classifier.

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Improving activity recognition of mobility-impaired stroke patients using wearable barometric pressure sensor

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Abstract

Background

Stroke survivors often suffer from mobility deficit. Current evaluation methods, including questionnaires and motor function tests, cannot provide an objective measure of the mobility capacity of patients in daily-life. To quantify unobtrusively this capacity, a minimal sensor configuration, such as a trunk-worn wearable sensor, is required. Existing approaches suffer from performance limitations due to the inter-patient variability of kinematic patterns during activities of daily-living (ADL) and particularly at the transition period between different activities. These limitations hence call for an additional sensing technology: barometric pressure (BP), an estimate of absolute altitude.

Methods

Our study aims at integrating BP into an activity classifier as a way to improve the recognition of major ADL (*Sit*, *Stand*, *Walk*, *Lie*) and corresponding activity level (Level, Up, and Down) for Stand and Walk activities. Data were acquired from 12 stroke patients, suffering from mobility deficit, with a BP-augmented inertial wearable sensor placed on their trunk. To benefit from the changes of elevation during postural transition (sit-to-stand, stand-to-sit), an event-driven activity classifier based on Fuzzy-Logic was devised. The events include the detection of Walking and Lying periods and potential postural transitions. These events were then fed into a double-stage hierarchical Fuzzy Inference System. While the first stage processed the events to infer activities, the second stage improved the ADL recognition by applying biomechanical constraints. Finally, the activity level was further characterized using a decision tree and a pattern-enhancing sinus-fitting algorithm applied on BP. Patients were videotaped for reference and typical metrics such as F-score and correct classification rate (CCR) were computed for validation. This classifier was benchmarked against a previously-published Fuzzy-logic-based algorithm and a conventional epoch-based data-driven classifier.

Results

For the recognition of ADL, the CCR was 90.6% for the devised algorithm, an improvement of +5.8% with respect to the epoch-based classifier. The proposed classifier essentially benefits from a better recognition of Sit activity (70.3% versus 42.5%). The activity level algorithm also achieved a high CCR (98.2%).

Conclusion

Combing BP with an event-driven activity classifier significantly improves the ADL recognition, and it is hence a powerful complement for unobtrusively monitoring activities in daily-life.

***Keywords*— activity monitoring, inertial sensors, activity of daily-living barometric pressure, stroke, mobility impairments, hierarchical fuzzy inference system?**

I. Introduction

Stroke impacts approximate 17 million people worldwide every year {feigin}. Post-stroke survivors are mostly affected by mobility disorders, such as hemiplegia, consecutives to lesion in the motor cortex following a stroke which require intensive physical rehabilitation. Current therapy adjustments are often based on clinical assessments including questionnaires such as the SF-36 or Stroke-specific QoL [1], or motor function test such as the BBS for balance assessment [2] or Timed Up and Go for gait and balance evaluation [3]. However, these tests are either subjective, in case of questionnaire, as they depend on the patient's perception of the questions and their state-of-mind during the test and/or can only be performed in a hospital setting. Due to the mentioned limitations, these clinical tests may not reflect the actual motor capacity of patient in daily-life, i.e., the patient's ability to perform certain mobility-related tasks at home, despite its usefulness in adjusting the rehabilitation strategy.

Monitoring major daily activities unobtrusively in home environment has been extensively investigated over the past few years along with the development and spread of wearable technologies. Daily activities were successfully monitored using a set of multiple sensors placed at key body locations [4], even for a post-stroke patient population [5],: trunk for detecting lying and walking periods, and later for characterizing postural transfers such as Sit-to-stand and Stand-to-sit (STS) transitions [6], a relevant outcome parameter for post-stroke recovery assessment [7] [8]; thigh for distinguishing sitting from standing posture; shank/foot for fine-grained gait evaluation. However, placing multiple sensors on the patient's body may lead to discomfort and hence hinder patient's ability and willingness to perform daily-activities as usual during the monitoring period.

For comfort, single sensor solutions were also used in some studies [9, 10] [11] for classifying basic activity of daily living. Although they are very accurate at recognizing dynamic activities (walking and running versus standing and sitting), they remains limited at classifying static postures (standing vs sitting), due to, for instance, a sensor placed on the thigh cannot distinguish sitting from lying posture. Furthermore, a trunk-located sensor can distinguish various major daily-life activities (lying, sitting, standing, and walking) but with restricted performance, due to the variability of movement pattern across activities and patients. This calls for an additional sensor modality such as barometric pressure (BP). BP provides an estimate of the sensor's absolute altitude which can be particularly useful to distinguish activity transitions involving altitude changes such as postural transition. However the most-common approach [12] in activity monitoring splits the data into fixed-time epochs and apply machine learning techniques for classifying each epoch into activity. Unfortunately, this approach is not well-suited as it cannot leverage the knowledge provided by the BP at the transition point.

Another approach, though less popular, consists in driving the activity recognition algorithm through events such as postural transitions, detection of walking or lying periods. Following this approach, Salarian et al. [13] incorporated postural transition-specific knowledge into a Fuzzy-Logic based activity recognition algorithm as a way to improve the activity recognition. However this approach did not account for BP and did not include biomechanical constraints which may improve the activity recognition. Furthermore, evaluating patients' mobility while climbing the stairs is also a very interesting outcome for post-stroke recovery [14] . [15] et al. proposed BP-based stair climbing detection algorithm but the results were only validated on healthy controls.

In this paper, a trunk-worn wearable activity monitor using a new Fuzzy-Logic based activity classifier is presented. The classifier fuses information from inertial and BP sensors, accounts for population-specific biomechanical constraints, and provides level (up and down) information about standing and walking activities.

II. METHODS

This section first describes the data collection protocol carried out on a mobility-impaired stroke population. Then, the wearable measurement/monitoring system, the Hierarchical Fuzzy Inference System (H-FIS), and the different algorithm the H-FIS was benchmarked against are detailed. Furthermore, the validation procedure is specified.

A. Data collection

The data were collected at the Kliniken Valens rehabilitation center (Valens, Switzerland), on 12 mobility-impaired stroke patients (7 Females and 5 Males / Age=59.6±13.6 y.o. / Height = 170.1±9.10 cm / Weight=73.9±14.1 kg) suffering from hemiplegia. Eight out of twelve patients were able to walk independently and four patients were walking with assistance such as a cane or a rollator.

Each patient was equipped with a set of wearable sensors and performed daily-life activities as instructed by the physician, for approximately 30 min (33.4 ± 9.4 min) depending on patients' fitness conditions. The target was to include a set of basic activities of daily-living: short and long walking episodes, walking up and down the stairs, taking the elevator, postural changes between lying, standing and sitting with and without arm movements. Various seats were included in the activity path: arm chair, bed side, sofa, armless chair, and stool. The set of daily-life activities included: walking along a corridor, watching TV, washing hands, eating, pouring and drinking water and, sleeping, shoe lacing, reading the newspaper, and putting on and off the jacket. These activities were suggested in a naturalistic way [16], i.e., in such a way that flexibility was given on how to perform the desired activities. For instance, the simple activity such as "watching TV" requires for the patient to walk towards the TV area, sit down on the sofa, use the remote control for turning on the TV and relax while watching TV. Furthermore, the number and the order of the instructed activities were not scripted in advance. During the trial, each patient was videotaped for validation. The study was approved by the ethical committee (St Gallen, Swiss Canton)

B. Measurement system and validation reference

During the data collection, the measurement system consisted of a small wearable sensor module (Physilog® 10D Silver, GaitUP, CH) placed on the patient at trunk (sternum) location. The device recorded to an on-board memory card the signals from an inertial sensor (3D accelerometer and 3D gyroscope) at 200Hz, and from a BP sensor at 25 Hz. The precision of the BP sensor is 1.2 Pa (~10 cm) according to the manufacturer's datasheet [17]. The signals from the accelerometer, the gyroscope and the BP sensors were first resampled at the same frequency of 40Hz to allow for faster processing. This frequency is still high enough to extract activity features [9, 18]. Moreover, the wearable sensors were aligned with the body segments by a calibration procedure based on two defined postures: lying down on a bed and standing upright against a wall. This procedure was necessary to ensure robustness against sensor misalignment across patients [19].

C. Recognition of activities and activity levels

Unlike epoch-based classifier, the event-based activity classifiers relied on events such as the detection of walking and lying periods and STS postural transitions. These events were then processed through a two-stage H-FIS to classify the activities into major daily-life activities: *Lie*, *Sit*, *Stand*, and *Walk*. The *Stand* and *Walk* activities are further split according to their activity levels: (level) Stand, Elevator Down (Standing with a downwards elevation change), Elevator Up (Standing with a upwards elevation change), (level)

Walk, Walk Downstairs, Walk Upstairs.

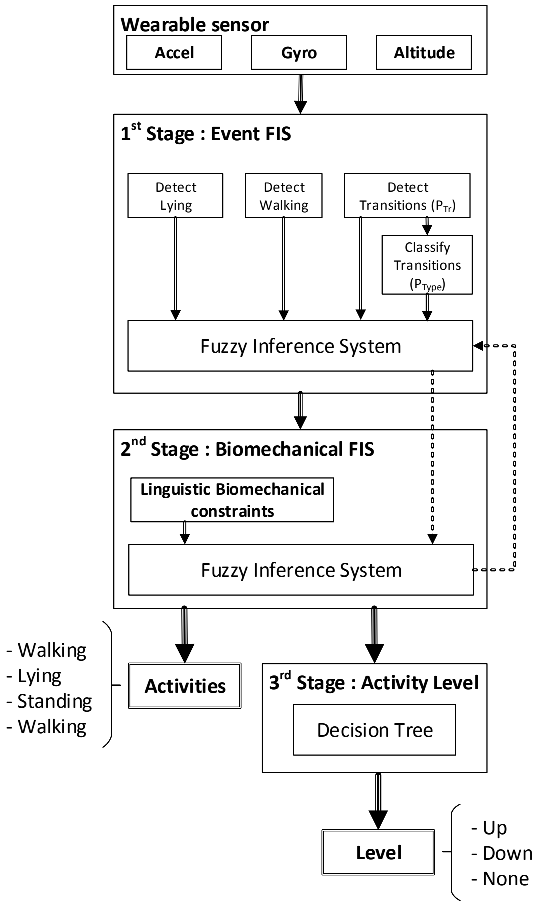

Figure 1 - Activity recognition algorithm: Architecture

1) Event detection and characterization

a) Lying and walking periods

Lying periods were identified using the trunk angle (with respect to gravity) estimated from the vertical axis of the acceleration signal. If this angle drops below a certain threshold θ_{Lying}=45° for more than a certain lapsed time ΔT_{Lying_in}=10 seconds, a lying period is detected until this angle goes above θ_{Lying} for more than ΔT_{Lying_out}=10 seconds.

Outside of those lying periods, walking periods were detected based on the algorithm devised by Salarian et al. [13]. This algorithm works as follows. First, the norm of the trunk acceleration is band-pass filtered from 1Hz to 5Hz using a 2nd-order Butterworth filter. Second, peaks from the filtered signal located above the threshold $\Delta\hat{a}_{walking}$ and separated from at least the time threshold $\Delta T_{walking\_steps}$ correspond to heel strikes during walking . Third, consecutive heel strikes within the time threshold $\Delta T_{walking\_group}$ are grouped together to form a walking period.

b) STS Postural transitions

The STS postural transition and characterization relied on an algorithm [20] that first extracted potential (or candidate) transitions from the wavelet-filtered trunk angular velocity in the sagittal plane. Then at the time of the transition, the algorithm modeled (sinus fitting) the (noisy) barometric pressure signal and extracted distinct features from the inertial sensors. A minimized set of these barometric and inertial features, described in Table 1 and Figure 2, were used to estimate two probabilities using logistic regression: 1) the probability P_{Tr} of a candidate transition to be an actual transition (0=False transition / 1=Actual transition); and 2) the probability P_{Type} of a candidate transition to be either a Sit-to-Stand or a Stand-to-Sit transition (0=StSi / 1=SiSt). Further information related to the transition modeling was available in the next section about the recognition of activity level.

2) Hierarchical fuzzy-based activity classifier

A fuzzy inference system is generally defined by a set of membership functions to transfer its inputs into fuzzy (linguistic) variables, a set of "If-Then" rules to fuse the fuzzy variables, an aggregation operator, and finally a defuzzification method. The Hierarchical FIS (H-FIS) was initially designed for the control of complex system [21] and consisted in a cascade of several FIS for which the most influential system variables are used by the first level, the next most influential variables at the second level and so on. This cascade of FIS was meant to in order to reduce the number of rules in the system.

The presented H-FIS was composed of only two stages, as described in Figure 1. While the first stage (Event FIS) was in charge of translating the events into activities, the second stage (Biomechanical FIS) was designed to apply linguistic biomechanical constraints for improving the recognition of activities as inferred in the first stage. They were both implemented as Mamdami FIS.

a) Event FIS

The following inputs were used in the Event FIS: *PrevAct*, the previous activity; *CurrAct*, the current activity; *TransitionDetection*, the postural transition detection probability (P_{Tr}); *TransitionType*, the postural transition classification probability (P_{Type}); and *AltitudeChange*, the altitude difference during the transition computed by averaging 20 seconds of the altitude data, derived from the barometric pressure: from 10 seconds before the transition up to 10 seconds after the transition. Only one output was defined in accordance with the activity inferred after the first stage.

The membership functions are described in Figure 2. This set of membership functions enabled describing the different states the fuzzy variables were in. Five membership functions were defined for the fuzzy variables *PrevAct* and *CurrAct* depending upon the considered activities: Lie, Sit, Stand, Walking and Unknown. Another membership function was defined as "SitOrStand" for the second stage. Two membership functions were defined, similarly as in [13], for both *TransitionDetection* and *TransitionType* corresponding to the different probability levels P_{Tr} and P_{Type}. The four membership functions defined for the input *AltitudeChange* were designed as trapezoidal with slopes accounting for the precision of the barometric pressure sensor.

The rules are presented in Table 1~~Table 1~~. As an example, the 5th rule from Table 3 should be read as: "If the *PrevAct* is *Sit* AND *CurrAct* is *Unknown* AND *TransitionDetection* is *Transition* AND *TransitionType* is *SiSt* THEN *EventActivity* is *Stand*". Furthermore, rules for the Lying-to-sitting and Lying-to-standing were added as the logistic regression-based transition models did not account for these transition types.

The aggregation was done by computing the minimum value across the fuzzy variables as defined by the rules. The defuzzification was done by computing the centroid of the fuzzy output. The CurrAct was initialized as *Lie*/*Walk* if a Lying/Walking period was detected or as Unknown otherwise.

Table 1 - Fuzzy rules for the Event FIS

PrevAct	*CurrAct*	*TransitionDetection*	*TransitionType*	*AltitudeChange*	***EventActivity***
	Lie				**Lie**
	Walk				**Walk**
Lie	Unknown			Very Positive	**Stand**
Lie	Unknown			Not Very Positive	**Sit**

Sit	Unknown	Transition	SiSt		**Stand**
Sit	Unknown	Transition	StSi		**Sit**
Sit	Unknown	No Transition			**Sit**
Stand	Unknown	Transition	StSi		**Sit**
Stand	Unknown	Transition	SiSt		**Stand**
Stand	Unknown	No Transition			**Stand**

b) Biomechanical FIS

The second stage consisted in applying biomechanical-inspired constraints to the output of the first stage in order to improve the overall classification performance. The following biomechanical constraints were considered while building the FIS rules set:

- It is likely that the activity detected in the previous stage is the true activity
- It is unlikely that a person stands still for more than $\Delta T_{standing}$ seconds without moving, i.e., no potential transitions and no walking/lying periods.
- It is unlikely that a person sits/stands for a long time and walks for a very short time and then sit back down for a relatively long time without moving.
- It is unlikely that a person walk for a very short time after lying, especially if there is no change of altitude.
- It is likely that if the activity detected at the previous is sitting or standing and there is a high change of altitude during the activity, the activity is standing (going up/down the elevator)

These linguistic rules can then be applied to a set of fuzzy variables, as displayed in Table 2~~Table 2~~ and Figure 2. To address this set of linguistic rules, the following inputs were added. *NextAct* accounts for the next activity as computed by the previous stage and share the same membership functions as *CurrAct*. *PrevDur*, *CurrDur*, and *NextDur* corresponds the duration of the previous, current and next activity respectively. Four membership functions were also defined to account for different type of activities: *VeryShort* (0s to 7s) for spurious activities than may need to be filtered out; *Short* for slightly longer activities (0s to 30s); Long for activities such as walk/stand and *VeryLong* for resting activities. *TrunkSTD* correspond to the standard deviation of the norm of acceleration during the activity. It can help in discriminating standing from walking in case the walking algorithm could not find a heel strike. Three membership functions were associated with *TrunkSTD*: Low, Medium and High. Furthermore, *AltitudeIQR*, the inter-quartile range (IQR), was computed from the altitude signal during the activity. These fuzzy variables were essentially introduced to prevent Elevator (*Stand*) activities to be misclassified as Sit.

For this stage the mean of maximum is used to aggregate the rule outputs. The output for this stage was then fed back to the first stage to re-classify the next activity based on the newly-classified current activity.

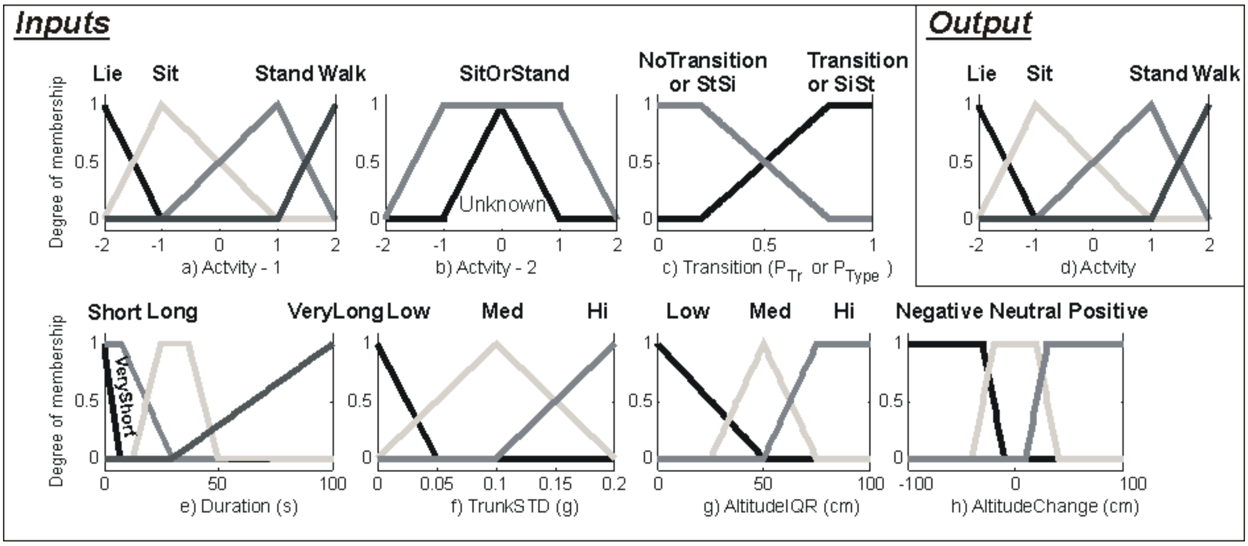

Figure 2 - Description of the membership functions. For clarity, the "Activity" fuzzy variable is split in two graphs : "Activity -1" and "Activity -2".

Table 2 - Fuzzy rules for the Biomechanical FIS

PrevAct	*CurrAct*	*NextAct*	*PrevDur*	*CurrDur*	*NextDur*	*TrunkSTD*	*AltC*	*AltIQR*	***Wt***	***Activity***
	Lie								**0.5**	**Lie**
	Walk								**0.5**	**Walk**
	Sit								**0.5**	**Stand**
	Stand								**0.5**	**Sit**
Sit		Sit	NotShort	V.Short	NotShort				**1**	**Stand**
Walk	Sit	Walk	Short	V.Short	Short				**1**	**Walk**

Walk	Stand	Walk	Short	V.Short	Short	High			**1**	**Walk**
Stand		Stand	NotShort	V.Short	NotShort				**1**	**Sit**
Sit	Walk			V.Short			Neutral		**1**	**Sit**
Lie	Walk			V.Short			Negative		**1**	**Lie**
	SitOrStand							High	**1**	**Stand**
	Stand				V.Long				**0.75**	**Sit**

3) Activity level classification and altitude fitting

An activity (e.g. *Stand*) may combined a subset of level (level standing) and non-level (e.g. Elevator Up) activities, a narrowing of the activity level is required. However, the patient's slow dynamics during stair climbing combined with the low signal-to-noise ratio and the influences of external perturbations of the BP sensor render the recognition of these activities difficult and thus requiring pattern enhancing techniques such as sinus fitting. In a third stage, a short decision tree combined with a sinus fitting algorithm was built to detect the activity level: level walking, going upstairs/downstairs for Walking activity; and standing still, take the elevator up/down for the Standing activity.

The decision tree separates the activities featuring both [CurrDur greater than ΔT_{level}=10 seconds AND AltitudeIQR greater than ΔAlt_{level}=60 cm] with the rest of the activities. The first class was considered as non-level activities and was characterized further using the sinus fitting function described below. The BP signal was first converted to altitude (Alt) using the barometric formula [22], then the pattern of transition was enhanced using a sinusoidal fitting model (S_{Alt}) [22] as follows:

$$S_{Alt}(t) = \Delta_{Alt} * E\left(\frac{t - Alt_{delay}}{Alt_{duration}}\right) + Alt_{drift} * t + Alt_{offset}$$
$$with\ E(t) \begin{cases} -1/2 & if\ t \leq -1/2 \\ 1/2 * \sin(\pi t), & if -1/2 < t \leq 1/2 \\ +1/2 & t > 1/2 \end{cases} \qquad (1)$$

The model was fitted using the "Trust-region reflective" optimization algorithm. The model parameters Δ_{Alt}, $Alt_{duration}$, and Alt_{offset} were set in order to smooth the BP signal and parameters Alt_{drift}, Alt_{delay} were bounded to account for the datasheet specifications of the BP sensor (MS5611-BA01, Measurement Specialties).

D. Benchmarked algorithms

1) Epoch-based algorithm

Epoch-based algorithm (EPOCH) was inspired by a recent algorithm [15] which processes the data as follows. It first splits the data into N_{epoch} epochs of ΔT_{epochs}=5 seconds and then features from each epoch are extracted. The feature set consisted in 120 (frequency, amplitude and temporal) features derived from the inertial (gyroscope and accelerometer) sensors. To avoid over-fitting, the feature set is reduced using ReliefF algorithm [23] to K features to form the minimal feature set $\boldsymbol{\Omega}_{epochs}$ = {N_{epoch} x K features}. These features are then fed into a machine learning classifier (Classification tree) {Coppersmith}. Following the leave-one-patient-out cross-validation procedure described in the validation section, each epoch is finally classified as either *Walk*, *Lie*, *Sit* or *Stand*.

2) Fuzzy-based algorithm

The FIS described in Salarian et al. [13] was essentially designed to compensate for classification errors in the recognition of postural transitions. It uses a subset of the previously described fuzzy variables and membership functions. Although it uses the same events (walking/lying periods and STS transitions), the logistic regression used for computing the probabilities $P_{Tr}^{inertial}$ and $P_{Type}^{inerital}$ only relied on inertial sensors.

E. Metrics for validation

1) Comparison strategy

The goal of comparing the activity recognition classifiers is to show the discrepancies between the different approaches: H-FIS versus State-of-the-art FIS as described by Salarian et al. versus epoch-based "tradition" data-driven modeling approach. However the goal of evaluating the activity level classifier consists in showing the value of using a sinus fitting function in an event-based activity recognition algorithm, the classifier comparison strategies hence differ.

a) Activity

Five classifiers, requiring different validation procedures, were assessed and compared for the activity recognition, as summarized in Table 3. The classifier #4 (S-$FIS_{inertial}$) did not account for altitude features in the computation of the probabilities $P_{Tr}^{inertial}$ and $P_{Type}^{inertial}$. To fairly estimate the performance differences between a single FIS classifier (Salarian et al.) and a H-FIS, the classified #2 (S-FIS$_{all}$) used the probabilities P_{Tr} and P_{Type} were used instead of $P_{Tr}{}^{inertial}$ and $P_{Type}{}^{inertial}$, respectively, to remove the effect related to the classification improvements thanks to the use of altitude features in the computation of the probabilities.

Furthermore, the output of the Event FIS was also computed separately from the H-FIS to estimate the performance improvement by the second stage.

Table 3 - Classifier validation procedure for activity recognition: summary table

#	Classifier	Acronym	Sensors	Validation
1	Event+Biomechanical FIS	H-FIS	Inertial and barometric	Full dataset
2	FIS Salarian et al.	S-FIS$_{all}$	Inertial and barometric	Full dataset
3	Event FIS	E-FIS	Inertial and barometric	Full dataset
4	FIS Salarian et al.	S-FIS$_{inertial}$	Inertial	Full dataset
5	Epoc-based model	EPOCH	Inertial	Cross-validation

b) Activity Level

The goal being to assess the value of the sinus fitting function for event-based activity recognition algorithm, three classifiers were evaluated:

- H-FIS as described in the previous paragraph with the activity level recognition algorithm described in II.C.3), including the sinus fitting function.
- the H-FIS excluding the sinus fitting function
- The epoch-based reference algorithm [15] with a feature set augmented with altitude features such as the IQR, standard deviation, range of the altitude signal during the epoch.

2) Validation procedure

Each patient was videotaped during the trial with a camera synchronized with the wearable system. The video recordings were manually annotated to form $\Omega_{reference}$, the reference activity set.

On one hand, the FIS-based activity classifiers were validated against the full dataset (no training/testing dataset split) as no parameter required to be learnt to build the FIS. On the other hand, the epochs-based classifiers were cross-validated using the procedure described below.

The performance of the epochs-based algorithm was evaluated using a 10-fold cross-validation procedure

[24]. During this procedure, the minimized feature set Ω_{epochs} was divided into N subsets (cross-validation folds) to be used for the training-testing procedure, N being 10. For each cross-validation fold, the feature sets from N-1 folds were included in the training set and the feature values from the remaining subset (different for each fold) were included in the testing set.

3) Classifier comparison

From the validation procedure described before, a confusion matrix is built for each classifier. Various metrics are extracted from these confusion matrices including: True Positive Rate (TPR also called Recall or Sensitivity – SEN –), True Negative Rate (TNR and also called Specificity – SPE –), Positive Predictive Value (PPV and also called Precision), Positive Predictive Value –, Negative Predictive Value (NPV), and the Correct Classification Rate (CCR). These metrics are thoroughly described in [25].

The classifiers were first compared globally by aggregating the confusion matrices together across all the patient sets. Secondly, and only for comparing the activity recognition algorithms, the algorithms were evaluated statistically using the non-parametric Friedman's test with the assumption that each patient set is independent.

III. Results

The results are presented with two granularity levels for each of the five benchmarked approaches. First data from all the twelve patients were aggregated into a single dataset and overall metrics were computed. Second, each patient's dataset was considered separately and significance statistics were computed.

A. *Overall performance*

1) Activity

The confusion matrices are presented in Table 1 along with the evaluation metrics. The H-FIS approach outperformed the S-FIS$_{inertial}$ by +3.5%, the S-FIS$_{altitude}$ by +1.2% and the EPOCH by +5.8%. This is mostly due to an improvement of the F-score (from +2.5% up to +28.4%) for the *Stand* activity, consecutive to an improvement of NPV (from +3.5% up to +13.1%) while the sensitivity remains at approximately the same level. Furthermore, the effect of adding information such as the biomechanical constraints improves by 9.7% the overall accuracy essentially provided my better distinction between sitting and standing posture from the H-FIS to the FIS approach.

Table 4- Confusion matrices for the recognition of the activities along with the corresponding evaluation metrics. Each confusion matrix is expressed in seconds. SEN = Sensitivity, SPE = Specificity, PPV = Positive Predictive Value, NPV = Negative Predictive Value, CCR = Correct Classification Rate

		Classification									
		Lie	**Sit**	**Stand**	**Walk**	**SEN**	**SPE**	**PPV**	**NPV**	**F-score**	**CCR**
		#1 H-FIS : Event+Biomechanical FIS									
Reference	**Lie**	1023.7	35.4	2.8	12.2	95.3%	99.7%	94.3%	99.8%	94.8%	**90.6%**
	Sit	40	11962.7	735.3	297.5	91.8%	95.6%	96.1%	90.7%	93.9%	
	Stand	22.2	245.3	2045.4	249.5	79.8%	94.6%	63.7%	97.5%	70.9%	
	Walk	0	203.8	425.6	6740	91.5%	96.6%	92.3%	96.2%	91.9%	
		#2 -FIS$_{all}$									
Reference	**Lie**	1022	21.1	17.1	13.8	95.2%	99.7%	94.5%	99.8%	94.8%	**89.4%**
	Sit	37.3	11729.9	940.9	327.4	90.0%	95.4%	95.9%	88.9%	92.8%	
	Stand	22.2	249.8	2060.6	229.8	80.4%	93.4%	59.2%	97.6%	68.2%	
	Walk	0	230.1	461.7	6677.6	90.6%	96.6%	92.1%	95.9%	91.4%	
		#3 - E-FIS : Event FIS									
Reference	**Lie**	1022	33.4	4.8	13.8	95.2%	99.7%	94.5%	99.8%	94.8%	**81.9%**
	Sit	37.3	9829.6	2841.2	327.4	75.4%	96.9%	96.7%	76.9%	84.7%	
	Stand	22.2	139.3	2171.1	229.8	84.7%	84.3%	39.2%	97.9%	53.6%	
	Walk	0	167.9	523.9	6677.6	90.6%	96.6%	92.1%	95.9%	91.4%	
		#4 - S-FIS$_{inertial}$									
Reference	**Lie**	1022	6.1	32.1	13.8	95.2%	99.7%	94.5%	99.8%	94.8%	**87.1%**

	Sit	37.3	11231.1	1439.7	327.4	86.2%	95.4%	95.7%	85.3%	90.7%	
	Stand	22.2	301.7	2008.7	229.8	78.4%	90.9%	50.6%	97.2%	61.5%	
	Walk	0	201.9	489.9	6677.6	90.6%	96.6%	92.1%	95.9%	91.4%	
		#5 - EPOCH : Epoch-based									
Reference	**Lie**	892	120	28	24	83.8%	99.3%	84.5%	99.3%	84.2%	**84.8%**
	Sit	124	11980	608	484	90.8%	83.1%	86.5%	88.3%	88.6%	
	Stand	40	1264	908	348	35.5%	96.3%	53.0%	92.7%	42.5%	
	Walk	0	484	168	6752	91.2%	94.9%	88.7%	96.1%	90.0%	

2) Activity level

The activity confusion matrices and evaluation metrics are presented in the table 5 for comparison between the EPOCS and the H-FIS, both with and without using the altitude sinus fitting function. While the H-FIS performed better in terms of overall accuracy (98.2%), it was essentially due to a high F-score which reached 76.1% on average for the four activity levels. The average F-score was 64.6% for the H-FIS (without sinus-fitting) approach and only 53.8% for the EPOCH approach.

Table 5 - Confusion matrices after the classification of the activity levels along with the corresponding evaluation metrics. Each confusion matrix is expressed in seconds

		Classification						
		None	**Elevator Up**	**Elevator Down**	**Stairs Down**	**Stairs Up**	**F-Score**	**CCR**
		#1 - H-FIS – with altitude sinus fitting						
Reference	**None**	23074.8	54.8	84.2	33.4	52.8	**99.1%**	**98.2%**
	Elevator Up	24.1	141.5	0	0	0	**78.2%**	
	Elevator Down	10.5	0	206.3	0	0	**81.3%**	
	Stairs Down	111.7	0	0	166.3	0	**69.6%**	
	Stairs Up	70.1	0	0	0	188	**75.4%**	
		#2 - EPOCHS						
Reference	**None**	23176	36	24	32	32	**98.8%**	**97.4%**
	Elevator Up	80	104	28	0	0	**51.5%**	
	Elevator Down	36	52	80	0	0	**53.3%**	
	Stairs Down	144	0	0	120	0	**57.7%**	
	Stairs Up	168	0	0	0	112	**52.8%**	
		#3 - H-FIS – without altitude sinus fitting						
Refere nce	**None**	22605.4	246.5	189.6	138.3	120.2	**98.3%**	
	Elevator Down	2.8	162.8	0	0	0	**54.6%**	

	Elevator Down	0	21.8	195	0	0	**64.8%**	
	Stairs Down	57.6	0	0	208.6	11.8	**66.8%**	
	Stairs Up	37.7	0	0	0	220.4	**72.2%**	**96.6%**

B. Statistical analysis

In the overall performance section, the importance of improving F-score was highlighted. This is also emphasized in detailed results presented in the figure below which hence displays not only the CCR but also for the F-Score results. When analyzing the CCR statistics, although there is no significant difference between H-FIS and S-FIS$_{all}$ ($p=0.24$), a significant difference ($p<0.05$) in terms of CCR exists between H-FIS and the remaining models (E-FIS, S-FIS$_{inertial}$, and EPOCH). Furthermore, no significance can be drawn from S-FIS$_{all}$ and S-FIS$_{inertial}$. No significant difference exists between the three last models (E-FIS, S-FIS$_{inertial}$, EPOCH). However, for *Sit*, the F-Score of H-FIS approach is only significantly different with respect to the S-FIS$_{inertial}$ and the EPOCH whereas the one from S-FIS$_{all}$ is significantly difference only with the EPOCH's F-Score. Similar significance can be observed when computing the F-Score statistics about the *Stand* activities. For *Lie* and *Walk*, the F-score the epoch-based approach is significantly different with respect to the other approaches.

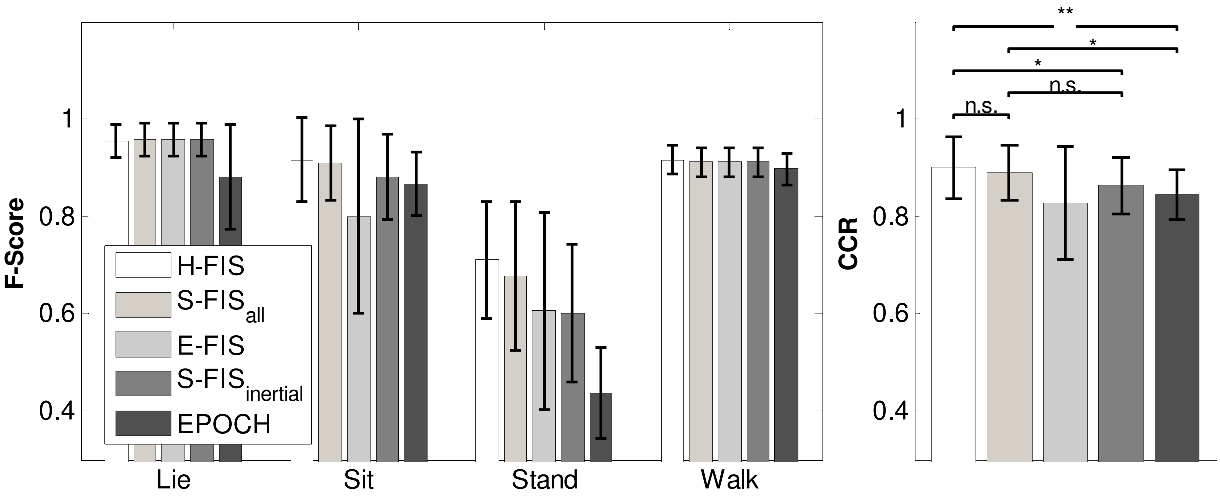

*Figure 3 - F-score (left) and CCR (right) computed for each approach. Bar height represents the mean and the error bar the standard deviation of the displayed metrics. ** = p<0.01 / * = p<0.5 / n.s. = p >0.5*

IV. Discussion

This paper presents a new activity recognition algorithm able to not only recognize the major daily-life activities (*Lie*, *Sit*, *Stand*, *Walk*) but distinguish also the activity levels: up and down the elevator for standing and up and down the stairs for walking. The recognition of human activity was carried out by an event-driven double-stage hierarchical fuzzy-logic inference system. While the first stage processed the events such as the detection of a postural transition, a lying or walking periods, the second stage improved the activity recognition by provided a simple ways to input biomechanical constraints. Five approaches were benchmarked on a dataset containing daily-living activities from 12 different patients suffering from post-stroke mobility disorders. The evaluation metrics included SEN, SPE, PPV, and F-score for all the activities and the overall performance accuracy. These metrics were also statistically evaluated using the non-parametric Friedman's test.

The results presented in this study demonstrate that models featuring BP sensor provides a better recognition of human activities (CCR of H-FIS 90.6%, S-FIS$_{inertial}$ 87.1%, and EPOCH 84.8%). This is essentially due to the fact that the event-driven architecture of H-FIS and the S-FISall enables to leverage the full potential of the barometric pressure at the activity transition time, i.e., during the potential altitude change. Furthermore, to the H-FIS approach results were statistically compared with others across patient-specific dataset. A statistical significance ($p<0.05$) was always found between H-FIS approach and the inertial-based approaches highlighting a significant improvements in the recognition across all patients ($N_{patients}=12$).

The dataset used in this study was composed of daily-activities performed at the clinic in naturalistic conditions. Ganea et al. highlighted the probable recognition performance lowering if those results were to be translated in "real" daily-life activity monitoring. This was mostly due to the fact that the performance in recognizing STS transitions was not high enough which is not the case in the present study thanks to the addition of BP. The pressure-based STS recognition is less prone to pathology related changes of trunk movement patterns.

The video recording was used for the validation. Providing the slow dynamics of the trunk, the annotation around an activity transition was difficult and this may have worsened the results. Furthermore, each period containing more than three consecutive steps were annotated as walking. However, the walking algorithm was initially developed for patients suffering from Parkinson's disease with consequent mobility deficits, and the algorithm may thus considered a slow walking period as *Stand* (F-Score of 70% for H-FIS). These factors may have adverse effect on the obtained results. Another limitation, occuring during the slow motion period within walking, is the lack of sensitivity at recognizing level walking from stair climbing. It was essentially due to the fact that a patient climbing the stairs might stall for few seconds which would then end the current walking session and start a new standing session and followed by a walking episode. These periods may not reach the required amplitude threshold ΔAlt_{level} and hence not classified as non-level activities. A solution could be either to have different threshold according to the non-level activities or to augment the decision tree with features from the inertial sensors.

Only the results from a descriptive machine learning algorithm was displayed (decision tree) as other epoch-based machine learning algorithms cannot also account for BP changes at the transition times. However, various machine learning algorithms were also tested using Weka [26] on the same feature-reduced dataset using the same 10-fold cross-validation procedure. They all resulted in an overall CCR for ADL recognition smaller than 87.5% (Decision Table: 85.5% CCR / Naïve Bayesian: 82.8% / Random Forest, #Trees=10: 87.5% / K-Nearest-Neighbors, K=10: 87.4%) confirming the selection of the event-driven algorithmic architecture.

V. CONCLUSION

To incorporate barometric pressure as a modality for the recognition of major activities of daily-living, a novel activity classifier was devised. It is based on a hierarchical fuzzy inference system for ADL recognition the activity and combined with a decision tree to and a sinus-fitting algorithm to classify the activity levels. The algorithm was benchmarked against a Fuzzy-logic-based state-of-the-art algorithm and an epoch-based classifier relying on machine learning techniques. On one hand, with a correct classification rate of 90.6%, the approach taken in this study outperformed all the others for the classification of ADL, essentially stemming from an improvement of the recognition of the Stand activity. One the other hand, the classification of activity level reached 98.2% for the H-FIS classifier. The high CCR values in both cases confirms the importance of integrating BP as a modality into a classifier and that the H-FIS approach is suitable for monitoring stroke patients unobtrusively.

Furthermore, splitting the activity classifier into three blocks, event processing, biomechanical constraints, and activity level recognition enabled a great modularity. Each of these blocks can be tuned according to the studied pathology. An extension of this work could not only to validate this approach on another patient population impaired by mobility restriction such as patient suffering from Parkinson's disease or chronic pain. Furthermore, optimizing the FIS membership function parameters using a global optimization algorithm or fusing the epoch-based algorithm with the H-FIS could also improve the performance of the presented system.

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